Machine Vision System for Inspecting Flank Wear on Cutting Tools

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Abstract—**This paper describes the development of a machine vision system for automated tool wear inspection. The proposed approach measures the tool wear region based on the active contour algorithm and classifies the wear type by means of neural networks. Test results show that prevalent tool wears can be checked robustly in a real production environment and therefore the manufacturing automation can be improved.**

Index Terms—**industrial image processing, machine vision, neural networks, tool wear, measurement**

I. Introduction

The current production tendency is the improvement of both production performance and quality levels in order to reduce costs and to avoid scrap. In the industrial manufacture flexible production systems with high performance and quality characteristics are required. Hence, the antiquated quality assurance method by measuring the specification conformity of a product at the end of the production line is replaced by a preventive quality strategy with inline-metrology [1]. Milling and turning are very common processes in industry today. Therefore, process monitoring of these machining processes has become of crucial importance to optimise production in view of quality and costs [1, 2]. Monitoring methods focus on the inspection of important process parameters, such as cutting forces, temperature and tool wear. Tool wear is usually the most relevant parameter inspected, as it has direct influence on the final product quality, the machine tool performance and the tool lifetime.

II. Cutting Tools and Tool Wear

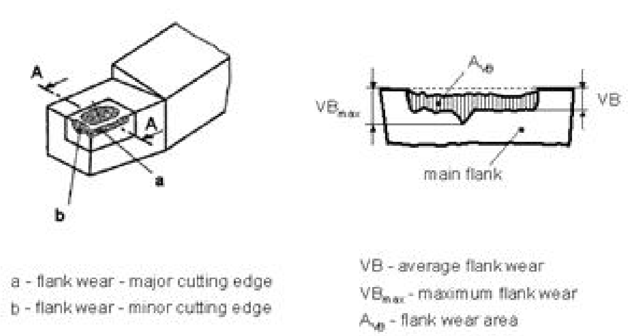


Figure 1. Flank tool wear and its parameters

The flank wear is the most referred tool wear parameter in the monitoring of machining processes – it allows to estimate the cutting tool's lifetime and to control the production process [2]. Fig. 1 shows the characteristics of flank tool wear. In ISO 3685 the measurement parameters (Fig. 1) for flank wear are defined [3]. The maximum flank wear value (VBmax) indicates the maximum appeared value for the flank wear – the maximum distance between the unworn cutting edge on the top of the tool to the bottom end of the flank wear land area. The flank wear value (VB) is defined as the average width of the flank wear land area. Additional to this, AVB describes the whole area of the flank wear land.

III. Related Work

Generally, the tool wear inspection is performed in three different ways [2] [4]. First, a statistical evaluation, based on estimated or FEM (Finite Element Method) simulated lifetime intervals is possible [2]. Second, process signals like the cutting forces or the acoustic emission can be used for a wear analysis [2] [5]. These indirect techniques try to evaluate the tool wear by inspecting the process data, which have a tight relationship with the tool wear. Third, a direct measurement on the cutting edge can be performed by using optical sensors [4] [6]. In [7] a strategy is developed for identifying cutting tool wear by automatically recognizing wear patterns in the cutting force signal. The strategy uses a mechanistic model to predict cutting forces under conditions of tool wear. This model is also extended to account for the multiple inserts. On the basis of predicted force signals linear discriminant functions are trained to identify the wear state of the process. In [8] [9] model-based approaches for tool wear monitoring on the basis of neuro-fuzzy techniques are presented. A model with four inputs (time, cutting forces, vibrations and acoustic emissions signals) and one output (tool wear rate) is designed and implemented on the basis of three neuro-fuzzy approaches (inductive, transductive and evolving neuro-fuzzy systems). The tool wear model is used for monitoring only the turning process. For the indirect techniques a precise and also computation-efficient model for predicting tool wear is essential. Machining processes (turning, drilling, milling, and grinding) performed by different machine tools are extremely complex and fraught with uncertainty. Therefore their behavior is practically difficult to describe exactly by modeling tools, even though approaches based on artificial intelligence techniques like fuzzy logic and neural networks are used. The direct methods deal directly with the measurement of the desired variable, thus usually providing a more precise result of the acquired signal. Currently, the first two values (VBmax and VB) are manually measured with microscope in industry [1] [2]. The top and

DOI: 01.IJCSI.03.01.13

bottom references for the flank wear region are determined by the worker subjectively. Hence, the measurement of the flank wear requires expert knowledge, is relatively time-consuming and its result is also strongly user-dependent [6]. Furthermore, it is not possible to quantitatively determine the area of the wear region (AVB) with microscope. In this context, the main objective of this research work is to develop a machine vision system for tool wear inspection on cutting tools. This automated system should realize a robust and fast flank wear measurement next to the production line. Based on the measurement, a reproducible wear type classification should also be realized.

IV. Machine Vision Prototype

The developed prototype consists of the following hardware modules: illumination unit, camera/optic-system and mechanical system.

A. Illumination Unit

Due to the different geometries and surface properties of cutting tools, a flexible illumination unit is required. To record all necessary information for the measurement and classification task, the illumination concept of the cutting tool inspection system employs a combination of three different lighting types: top light, half-ring light and side lights (Fig. 2). A dual-image acquisition under different illumination conditions enables an optimal detection and measurement of the flank wear.

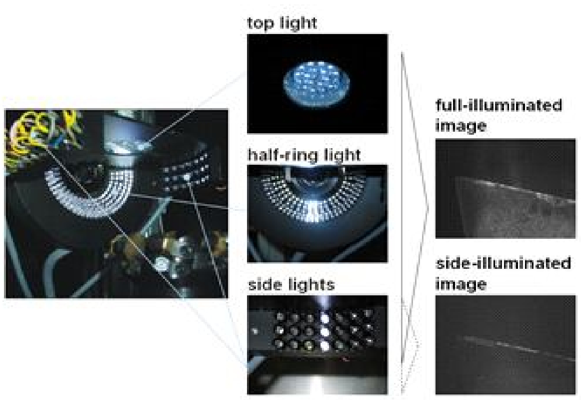


Figure 2. Developed illumination unit

First, a full-illuminated image of the worn cutting insert is taken for the detection of the tool area in image with all three lightings. Second, a side-illuminated image is acquired for the feature extraction of wear region and the final wear measurement solely with side lights (Fig. 2).

B. Camera/Optic-System

For the camera/optic-system, a monochrome CCD-camera with an effective sensor size of 752x582 pixels is used. In combination with an optical lens with a fixed focus length of 42 mm, a resolution of 4.4 μm is realized.

C. Mechanical System

For a flexible measurement of the flank wear, three motorized axes are required (Fig. 3):

- Z-axis: positioning the camera for tools with different heights;
- X-axis: driving the cutting tool head in camera focus for tools with different diameters;
- C-axis: rotating the tool for the positioning of all cutting inserts in the focus of camera.

After the placing the tool in a HSK 63A receiver in the reference position, the tool and camera are positioned adaptively to the tool geometry. During the rotation of C-axis, each cutting insert is detected automatically and finely tuned to a well-focused orientation. After successive image acquisition of all inserts, the tool is driven back to the reference position.

V. Image Processing Chain

To achieve the goal of an automated measurement of flank wear, the machine vision prototype was built with an image processing chain, which is developed to determine the VBmax, VB and AVB values for different kinds of tools (Fig. 4). The basic image processing tasks of the chain are the following: image acquisition, tool edge detection, highlighting wear region, feature extraction, wear type classification and finally wear measurement. Each of them consists of a certain number of image processing steps with special configuration parameters (Fig. 4).

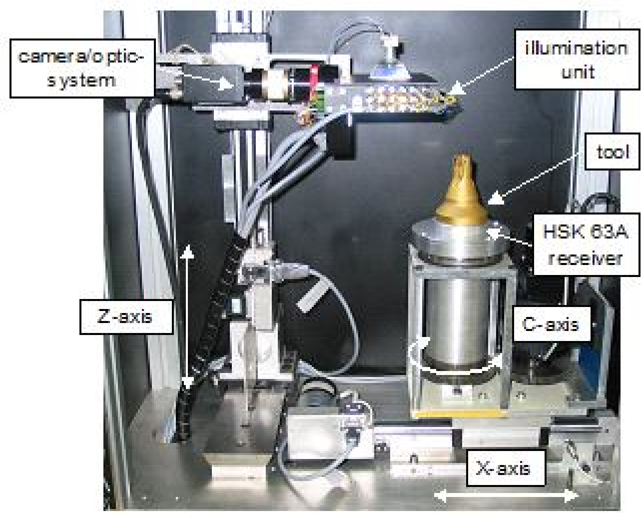


Figure 3. Machine vision prototype for tool wear inspection.

A. Tool Edge Detection

In order to measure the tool wear, it is only necessary to proceed tool area within the acquired image. The tool area could be separated from image background by finding the top and side tool edges in the full-illuminated image (Fig. 4, 2. column). To detect both edges, two ROIs (regions of interest) on each edge are predefined. The locations of the ROIs in the image are calculated based on tool type information (e.g. radius, length). After applying the Canny edge detector [10] to the image areas defined by ROIs, image pixels on tool borders are extracted. By fitting the sequence of detected points along the tool borders with a line function, the top and side tool edges are determined.

DOI: 01.IJCSI.03.01.13

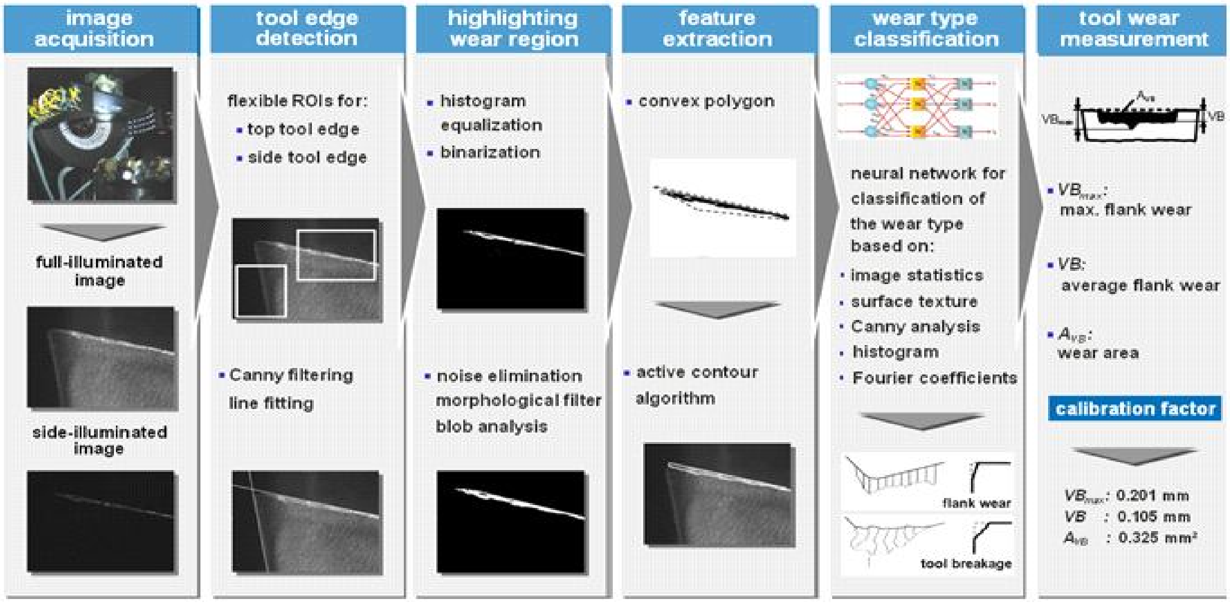


Figure 4. Image processing chain for the tool wear inspection system.

B. Highlighting Wear Region

First, automatic histogram equalization [11] is performed on the side-illuminated image, which results in the contrast enhancement of the wear region. A histogram is a graphical diagram that provides information about the frequency in which each brightness level appears in the whole image. A linear transformation in its brightness histogram achieves a better distribution of the brightness spectrum of the image, resulting in the enhancement of the wear area and in the improvement of the visual information of the tool. Subsequent to image thresholding, morphological filtering and blob analysis are applied to binarized image and used to eliminate the remaining noises in the image, leaving the wear area (Fig. 4, 3. column).

C. Feature Extraction

Depending on cutting conditions and duration, the tool wear could appear in different forms. In order to achieve a reliable tool wear inspection, the active contour algorithm [12] is used to extract the wear region, which detects the edges of regions with inconsistent shapes robustly. By iteratively minimizing system energy, this algorithm converges a chain to surround the whole tool wear region as closely as possible. Similar to [12], the following three part energy functions are used. The continuity energy is defined as

$$E_{cont} = \left|\alpha - \left|p_i - p_{i-1}\right|\right|, \tag{1}$$

where α is the mean distance between two points on the con-tour and p_i is the contour point. By a minimized energy function (1) equidistance between the contour points should be obtained.

The curvature energy is modeled by

$$E_{curv} = \left|p_{i-1} - 2 \cdot p_i + p_{i+1}\right|^2. \tag{2}$$

To minimize the curvature energy in (2), the angle between a contour point p_i and its two neighboring points p_{i-1}, p_{i+1} must be kept as straight as possible. This leads to a smoothing of the contour.

For the binary image, the image energy is set equal to the gradient of the image

$$E_{img} = -\left|grad(I)\right|. \tag{3}$$

where I is the pixel intensity. For the minimization of this energy, the contour must be attracted to such locations in the image, where the gray value varies strongly, such as region edges. For the active contour algorithm, the system energy is defined as weighted sum of above introduced energies

$$E = \alpha \cdot E_{cont} + \beta \cdot E_{curv} + \gamma \cdot E_{img}, \tag{4}$$

where α, β and γ are weights for the individual energies. With optimally adjusted weighting, the active contour algorithm tracks the edge of tool wear region dynamically and adaptively, considering its shape should be as regular and smooth as possible. A convex polygon, surrounding the wear region, is used as the initial estimation to start searching the wear contour by means of the active contour algorithm. At the end of the iteration, it provides the best set of points that represents the tool wear area contour (Fig. 4, 4. column).

D. Wear Type Classification

On the base of the extracted outer contour of the wear region, the classification of tool wear type is performed. A neural network based method is developed because of its ability to solve and generalize non-linear classification problems [13]. This work currently focuses on the two most important cases: flank wear and tool breakage (Fig. 4, 5. column). To build a distinctive description of the tool wear, the following features are extracted from the segmented wear region, which are tested as inputs for the neural network.

DOI: 01.IJCSI.03.01.13

• image statistics: average, maximum, minimum, standard deviation
• surface texture: average variance of gray values of the segmented area, which analyzes image textures of wear region
• Canny analysis: Canny filtering, which characterizes the high-frequency image details, such as edges and wear textures
• histogram: which describes the brightness of the wear region
• Fourier coefficients: the normalized 10 lowest coefficients without the constant component calculated from the outer contour, which give a translation and rotation decorrelated description of the contour of wear region

To find a good input-output function for the neural network, different feed-forward network topologies are tested. The best structure uses neurons with sigmoid output response [13], 14 inputs combined from Canny analysis and image statistics, a hidden layer with 10 neurons and an output layer with 2 neurons, each one for a specific wear type.

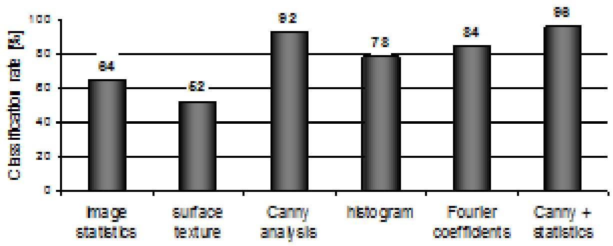


Figure 5. Results of tool wear type classification

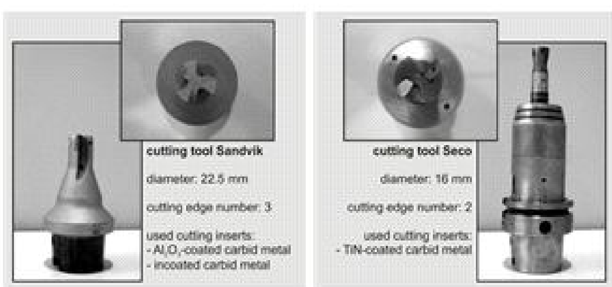


Figure 6. Test cutting tools

This network achieves an accuracy rate of 96% in classifying a set of 25 worn tools (Fig. 5). A back-propagation algorithm is used to train 15 sample pairs. The validation of the results is confirmed with a microscope, based on expert knowledge.

E. Tool Wear Measurement

After flank wear is detected, the measurement of its parameters is performed. According the ISO 3685 [3], the flank wear parameters VB and VBmax are evaluated as the perpendicular distances from the lower contour points to the top cutting edge. As introduced in section 1, AVB is the sum of all pixels in the wear area (Fig. 4, 6. column). These values are firstly calculated in number of pixels. To represent this parameter in the standard measurement unit, a calibration method based on [14] is applied to the image processing system. Using a checkerboard pattern, the transformation for correcting perspective is computed and radial lens distortions are compensated. With the accurate size of the checkerboard squares, the calibration factor of the designed prototype results in a value of 4.44 µm for each pixel in the image.

VI. Experimental Results

The measurement method is evaluated on real cutting tools, which have different geometries from different manufacturers. An example test set is given in Fig. 6. In order to evaluate the system, a set of five worn cutting inserts is used. For each cutting insert 10 test images are acquired. With this insert set a test for the tool wear measurement can be estimated from a sample of 5x10=50 test images of real cutting tools. In Fig. 7 the results of the example test set of cutting tools are presented. They are validated against the manual measurement with microscope, which is performed by tool specialists and used as reference. This comparison shows that similar measurement accuracy is achieved by the auto-mated machine vision system as expert measurement. Our analysis indicates that the deviation is caused by the dirt on the cutting. Based on a validation of inspection equipment applicability of this machine vision system according to the guideline QS 9000 (measurement system analysis, MSA) [15], the repeatability of the automated tool wear measurement is determined to 7.5 µm. Compared to the uncertainty of wear measurement with microscope (39.5 µm), the developed machine vision system can be classified after MSA as suitable for the inspection task.

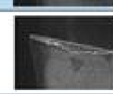
test tool	VB [mm] microscope	VB [mm] machine vision system	deviation [mm]
	0,129	0,145	0,016
	0,291	0,292	0,001
	0,122	0,149	0,027
	0,180	0,168	0,012
	0,045	0,055	0,010

Figure 7. Comparison of test results achieved by microscope and the developed machine vision system

Conclusions

This paper describes the development of a machine vision system for an automated tool wear inspection. The hardware requirements and software solutions are characterized. The experiments on real cutting tools show that the proposed prototype can achieve both accuracy and robustness for tool wear measurement and wear type classification.

DOI: 01.IJCSI.03.01.13

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DOI: 01.IJCSI.03.01.13